Offline Signature Verification Based on Bag-of-Visual Words Model Using KAZE Features and Weighting Schemes

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Abstract

The familiar use of handwritten signatures in various applications (e.g., credit card authentication) increases the need for automated verification methods. However, there is still room for improvement in the performance of automated systems under various writing conditions compared to human beings, especially forensic document examiners (FDEs). Furthermore, even with modern techniques, obtaining as much information as possible from the limited samples available remains challenging task. Therefore, further research is required to improve the performance of automated systems. In this study, to improve the performance of offline signature verification, a new approach based on a bag-of-visual words (BoVW) model is adopted. The novelty features of the proposed approach are following: 1) considering the cognitive processing of visual information by FDEs to improve the performance of offline signature verification, 2) using an approach based on the BoVW model to implement the FDEs' cognitive process for feature extraction, 3) incorporating weighting schemes based on term frequency-inverse document frequency to enhance the discriminative power of each visual word, 4) adopting KAZE features in the BoVW model to consider the contour information of strokes more effectively, and 5) detecting the KAZE features in both the strokes and background space to introduce not only the stroke itself but also the various relations between strokes. The promising performance of the proposed approach is shown by using an evaluation method with a popular CEDAR signature dataset.

1. Introduction

Handwriting is a dynamic and complex activity based on the combined coordination of various physical behaviors. It is widely known that no two writers share the same combination of handwriting features and that one person's handwriting used for the same material is consistent within a limited variation. Thus, handwriting has been considered as one of the most important security means related to human traits. These handwriting characteristics have been accepted as evidence for many important applications such as claims, wills, and contacts, especially in biometrics and forensic science. In biometrics, signature verification has been used as one of the most widespread means for authenticating writers from the behavioral characters [8, 9, 17, 20, 29]. In forensic science, automated signature verification also assists forensic document examiners (FDEs) in executing their examination tasks efficiently [11, 25–28].

Signature verification can be categorized into two types: online and offline methods. In online methods, the dynamic information (*e.g.*, pen location, pen inclination angles, and pen pressure) is used for analysis, while in offline methods, only static information from the signature image is used. Offline methods do not require any special instruments and are needed to recognize a person's identity when their signature is pre-written on paper; therefore, many automated methods have been proposed [8, 9, 17, 20, 29]. However, the performance of automated offline signature verification in various writing conditions is still much less successful than verification by human beings, especially FDEs [3, 14, 25]. Furthermore, even with modern techniques, obtaining as much information as possible from the limited samples available remains challenging task [15, 16]. The consequences of any inaccuracy in the results of a signature verification method pose serious problems. Therefore, further research is required to improve the performance of automated signature verification systems.

A promising approach is the consideration of the cognitive processing of visual information by FDEs. In forensic science, when comparing investigated signatures with reference ones, FDEs typically look not at the whole signature but at some local salient regions that have concentrated changes in pen movement using a bottom-up search strategy [4, 5, 19].

In this study, to improve the performance of offline signature verification, a new approach based on a bag-of-visual words (BoVW) model [10, 24], which has been widely applied in content-based image retrieval [10, 24], is adopted.

Following are the novelty features of the proposed approach:

1. Considering the cognitive processing of visual information by FDEs to improve the performance of offline signature verification.

2. Using an approach based on the BoVW model to implement the FDEs' cognitive process for feature extraction.

3. Incorporating weighting schemes based on term frequency-inverse document frequency (tf-idf) [10] to enhance the discriminative power of each visual word.

4. Adopting KAZE features [1] in the BoVW model to consider the contour information of strokes more effectively.

5. Detecting the KAZE features in both the strokes and background space to introduce not only the stroke itself but also the various relations between strokes.

The rest of the paper is organized as follows. Section 2 presents related work on offline signature verification. Section 3 presents the proposed approach based on the BoVW model. Section 4 reports experimental methods and results. Section 5 provides the conclusion.

2. Related work

To date, many signature verification methods have been proposed especially in biometrics and forensic science. In this section, after brief summary of offline signature verification methods using local feature-based approach, recent studies of forensic signature analysis are summarized.

2.1. Signature Verification in Biometrics

In biometrics, signature verification has been researched as a method of using behavioral traits to recognize a person [8, 9, 17, 20, 29]. Feature extraction techniques can be classified into two types: global and local features [8, 17]. Global features describe the signature images as a whole. In contrast, local features represent parts of the segmented signature images, obtained by applying feature extractors in each part of the image. Thus, local features that is resistant to global shape variation can provide detailed information on signatures.

Off late, local descriptors extracted from salient regions have been applied for signature verification. Scale Invariant Feature Transform (SIFT) [13] has been used on local interest points to construct a classifier for offline signature verification by using local and global matching procedures [21]. Speeded-Up Robust Features (SURF) [2] have been used to classify offline signatures by comparing the average keypoint level accuracy [18]. These methods have an advantage in real situations in that they can be applied even when a part of the signature is accidentally missing; however, they fail to extract the structural relations between descriptors and the feature vectors of fixed dimension.

2.2. Signature Analysis in Forensic Science

In forensic science, offline signatures written under various writing conditions have been investigated by FDEs mainly by microscopic and instrumental methods [11]. Automated signature verification also assists FDEs in executing their examination tasks efficiently [11, 25–28].

Among these methods, recent research using eye-gaze tracking technology reported FDEs' cognitive process of the visual attention when comparing signatures [4, 5, 19]. Dyer *et al*. [4, 5] reported that FDEs examined not a whole signature or all local regions equally, but focused on some salient local parts that had concentrated changes in pen movement, and the expertise was mediated how the viewed information was processed. Pepe *et al*. [19] summarized that signatures with a high complexity had longer observation times than ones with low complexity during signature simulating.

For now, there is still room for improvement in the performance of automated systems compared to human beings, especially FDEs [3, 14, 25]. Thus, considering the cognitive processing of visual information by FDEs is promising for automated offline signature verification.

In this study, to improve the performance of automated offline signature verification, a new approach based on the BoVW model [10, 24] is adopted. The BoVW model has recently been shown to be very capable of discriminating between small writing fragments for characterizing individuals from their handwritten documents [31]. However, to the best of my knowledge, this has not been used in offline signature verification research. Because the BoVW model uses local descriptors detected in salient regions while extracting the structural relations, similar to FDEs' examination process, it could also be effective for automated offline signature verification. To enhance the discriminative power, KAZE features [1], where KAZE is a novel multiscale 2-D feature detection and description algorithm in nonlinear scale spaces, and weighting schemes based on tf-idf [10] can then also be employed.

3. Offline Signature Verification Based on BoVW Model

Signature verification is a two-class classification problem used to determine whether an input signature is genuine or forgery using discriminative features. The proposed approach attempts to extract these features based on the BoVW model and to consider the cognitive processing of visual information by FDEs. Additionally, KAZE features

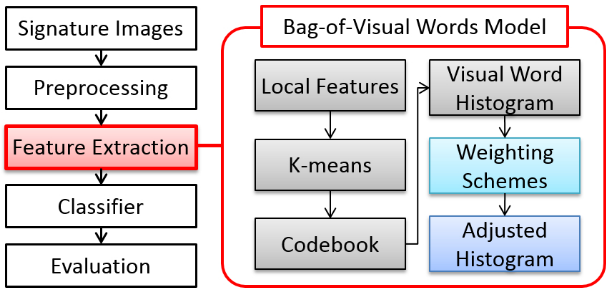


Figure 1. Outline of the proposed method.

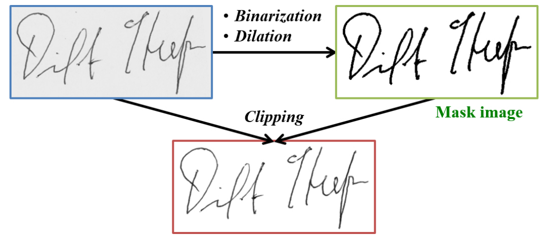


Figure 2. Stroke-clipping process.

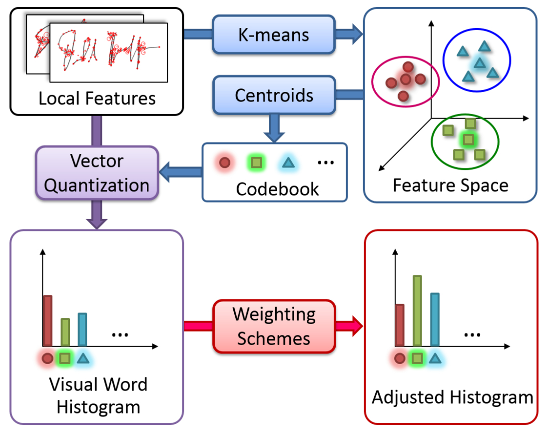


Figure 3. Outline of the proposed BoVW model.

and weighting schemes are employed to enhance the discriminative power of each visual word.

Figure 1 shows an outline of the proposed method. After obtaining signature images, preprocessing is applied to improve the position, rotation, and image quality of the signature. Simultaneously, a clipping of strokes from the images is applied to remove background noise. The features are then extracted using the BoVW model with weighting schemes. Finally, the support vector machine (SVM) is adopted to construct two-class classifiers for each writer using these features. The following subsections explain the details of sub-processes.

3.1. Outline

3.2. Preprocessing

To improve the position, rotation, and image quality of the signatures, preprocesssing is applied. Then, a moment-based normalization method is employed to regulate the position and rotation without deforming the structures of signature.

Here, the original image is low contrast, and the light and shade are also affected by some writing conditions such as the surface under the paper. Histogram normalization is then applied to the images. Some background noise can also disturb the analysis of feature extraction process. To overcome this, the strokes are clipped using a mask image as reported in [15, 16]. Specifically, the binarized image is created from the original gray-level image using a threshold technique based on linear discriminant analysis. To enhance the strokes, a smoothing filter and a dilation of strokes are also applied to it. Finally, the clipped images containing only strokes on a regular background are obtained (Fig. 2).

3.3. BoVW Model with Weighting Schemes

The BoVW model is inspired by a Bag-of-Words model, which is employed in information retrieval to describe a document as a set of words [10, 24].

The BoVW model for documents (i.e., signature images) comprises a set of visual words to describe the image content. A visual word is expressed by a set of features that correspond to salient local images detected as keypoints. Each local keypoint belongs to a visual word that corresponds to the cluster centroid using a k-means clustering algorithm. The set of all clusters defines a codebook as a visual word dictionary. Finally, the image is represented by a vector that denotes the corresponding descriptor, and reflects the frequency of each visual word that appears in the image.

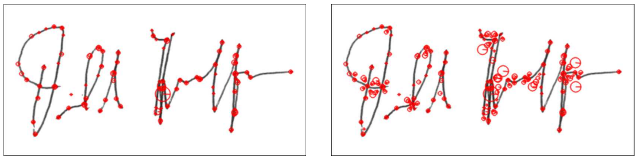
In this study, a weighting schemes is also incorporated in the BoVW model to consider the importance of each visual word. Figure 3 provides an outline of the proposed BoVW model.

Subsequently, the local features and weighting schemes are detailed.

3.3.1 Local Features

The local features are representations of salient regions of the image based on local extrema (*e.g.*, edges, corners, and blobs) [12]. Among them, most widely used local features are SIFT [13] and SURF [2]. Although SIFT is highly discriminant, its computation is relatively slow. Similar to SIFT, SURF relies on local gradient histograms. SURF adopts a Hessian matrix-based measure for the detector and Haar wavelet responses for the descriptor. By relying on integral images for image convolutions, the computation time is significantly reduced. In [10], SURF was shown to perform better than SIFT in the BoVW model.

Recently, KAZE features [1], which is a Japanese word



(a) Excluding the background (b) Including the background

Figure 4. Example of KAZE features. Red circles indicate the detected features.

meaning *wind*, have been proposed to detect the main orientation of the keypoint, and to obtain a scale- and rotation-invariant descriptor in nonlinear scale spaces by using efficient additive operator splitting techniques and variable conductance diffusion. Compared to previous Gaussian-scale space-based approaches that lead to image blurring, this method introduces nonlinear diffusion filtering to provide multiscale image spaces while preserving the natural image boundaries. The effectiveness of using features based on the contour information of strokes has been shown in signature verification [7]. The use of KAZE features is therefore a rational choice for offline signature verification.

Note that the local features can be detected not only from the signatures but also from the background near the strokes. Most papers that use descriptors of local features for handwriting have removed these descriptors in the background space [31]. However, the proposed method leaves them to consider not only the stroke itself but also the various relations between strokes (Fig. 4). The effect will be described in Section 4.2.

3.3.2 Weighting Schemes

To consider the importance of each visual word for signature verification, weighting schemes are incorporated into the BoVW model. The common weighting schemes are term frequency (tf) weighting, document frequency (df) weighting, and normalization [10]. The first factor, tf, is a weight defined as every term (i.e., visual word) in the codebook according to the number of occurrences in a document d. The second factor, df, is a weight assigned to the number of documents containing the term t. Then, the inverse document frequency (idf) is often used. Finally, the normalization is a method that adjusts the visual word histogram to a unit-length vector to eliminate length differences between documents.

The System for the Mechanical Analysis and Retrieval of Text (SMART) notation is a compact way to represent a combination of weighting schemes that consist of a form such as "aaa," where the first letter denotes the term frequency weights, the second term denotes the document frequency weights, and the third denotes normalization [10]. Table 1 presents the SMART notation for tf-idf weight variations. Here, $tf_{t,d}$ is the number of times a term t occurs in a document d, df_t is the number of documents that contain the term t, N is the total number of documents, and w_t is the weight of term t in the document, where the size of codebook is M. In the implementation process, after generating the visual word histogram for every signature through the BoVW model, the vectors are recalculated using all eight weighting schemes: "nnn," "nnc," "ntn," "ntc," "lnn," "lnc," "ltn," and "ltc."

Table 1. SMART Notation for Weighting Schemes

tf	df	Normalization
n(natural): $tf_{t,d}$	**n**(no): 1	**n**(none):1
l(log): $1 + \log(tf_{t,d})$	**t**(idf): $\log \frac{N}{df_t}$	**c**(cosine): $\frac{1}{\sqrt{w_1^2+\ldots+w_M^2}}$

3.4. Signature Verification with an SVM

The SVM is a powerful machine learning method for classification [30] and has been widely used in signature verification [15, 16, 18, 28]. Geometrically, SVM constructs a separating hyper plane with maximal margins based on the principle of structural risk minimization from statistical learning theory.

Assume that there is a set of labeled training instances $\{\boldsymbol{x}_i, y_i\}_{i=1}^N$, where $\boldsymbol{x}_i \in \mathbb{R}^d$ and $y_i \in \{-1, +1\}$ for $i = 1, 2, \ldots, N$. Given a nonlinear mapping function ϕ that transforms the input data to a higher dimensional feature space, a kernel function $K(\cdot, \cdot)$, a weight vector $\boldsymbol{w}$, a bias b, slack variables ξ_i, Lagrange multipliers $\alpha_i \geq 0$ and $r_i \geq 0$, and a penalty constant C that controls the trade-off between the slack variable penalty and the margin, the primal Lagrangian to be optimized is given as follows:

$$\begin{aligned} L =& \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{N}\xi_i \\ & - \sum_{i=1}^{N}\alpha_i[y_i(\boldsymbol{w}\cdot\phi(\boldsymbol{x}_i) + b) - 1 + \xi_i] - \sum_{i=1}^{N} r_i\xi_i. \end{aligned} \tag{1}$$

Here, the formula is subject to the Karush-Kuhn-Tucker (KKT) conditions as follows:

$$0 \leq \alpha_i \leq C \quad \text{and} \quad \sum_{i=1}^{N}\alpha_i y_i = 0.$$

The parameters of C and the kernel function are tuned using the simple grid search method in the experiments described in the next section.

3.5. Evaluation

In signature verification framework, two types of errors can occur: false rejection rate (FRR) and false acceptance rate (FAR). FRR corresponds to the genuine signature rate rejected by the verification system; FAR corresponds to the

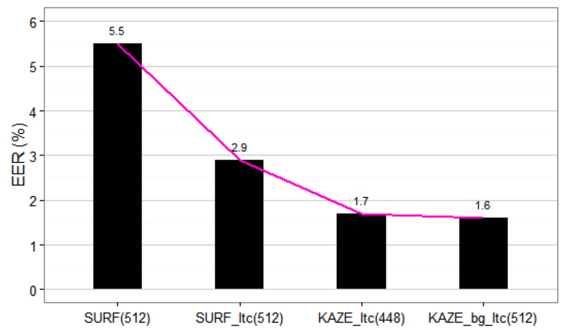


Figure 5. Overall performance of the proposed method. The values given in parentheses on the horizontal axis indicate the best number of visual words for each type of local feature.

fictitious signature rate accepted by the verification system. Because the two errors are inversely related, equal error rate (EER) is is calculated for the evaluation. EER corresponds to the operating point on the receiver operating characteristics (ROC) curve such that FAR equals FRR [29].

4. Experiments

4.1. Methods

To evaluate the performance of the proposed method, the CEDAR signature dataset [28], which has been widely used in signature verification research [6, 22, 23], was adopted. This dataset contains offline signatures from 55 volunteers. For each writer, 24 genuine and 24 skillfully forged signatures were provided (i.e., 1320 genuine and 1320 forged signatures in total). The scanned signatures are composed of 8-bit gray-level images at 300 dpi.

In all experiments, a 3-fold cross-validation strategy was applied. Specifically, each of the 24 genuine and 24 forged signatures were randomly split into 3 parts, and 1/3 of the data was repeatedly used as a test set and the remaining as a training set.

Additional important information includes the following:

- The radial basis function (RBF), whose effectiveness was shown in [15, 16], was used as the kernel function of the SVM:

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\gamma\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}. \tag{2}$$

- To tune the parameters (i.e., the penalty constant C and RBF γ), a grid search was applied.

- The length of the local descriptor vector was 64-D.

4.2. Results

4.2.1 Overall Performance

Figure 5 compares the EER of the proposed method to confirm the performance under various conditions: 1) the type of weighting schemes, 2) the type of local features (popular SURF and recent KAZE), and 3) the location of local features (detection of stroke features with/without the background space).

The results shown in Fig. 5 are as follows:

1. The EER of the original visual word histogram (SURF with "nnn" in SMART notation) was reduced by the weighting scheme "ltc" in the BoVW model ("SURF_ltc" in Fig. 5) from 5.5% to 2.9%. Here, "ltc" is selected as the best weighting scheme (Section 4.2.2).

2. The EER obtained using the KAZE features on strokes ("KAZE_ltc") decreased by changing the local feature SURF ("SURF_ltc") from 2.9% to 1.7%.

3. The EER obtained by additionally using the KAZE features from the background space ("KAZE_bg_ltc") further decreased from 1.7% to 1.6%.

These results confirm the effectiveness of the proposed BoVW model that adopts weighting schemes, KAZE features as local descriptors, and the detectors for both strokes and the background.

4.2.2 Effect of Weighting Schemes

Figure 6 depicts the influence of weighting schemes on the BoVW model using popular SURF and recent KAZE features while changing the number of visual words. We can confirm the effectiveness of each weighting scheme compared to the original visual word histogram (i.e., "nnn" in SMART notation). In total, the use of "l" (log) for tf tends to be more effective than that of "n" (natural). Finally, from the SMART notation for all three types of local features, the lowest EER was provided by "ltc," which means "l" (log) for tf, "t" (idf) for df, and "c" (cosine) for normalization.

4.2.3 Comparative Analysis

Table 2 shows the error rates of the proposed method and other previous reports [6, 22, 23, 28], which dealt with two-class offline signature verification strategies using the CEDAR dataset. Srihari *et al*. [28] used the gradient, structural, and concavity features with SVM. Shekar *et al*. [23] proposed a feature vector based on local morphological pattern spectra from eight equally sized vertical blocks of the signature image and used the Earth Movers Distance for signature verification. Ganapathi and Nadarajan [6] applied a feature vector based on the gradient direction of each pixel from across a signature with a fuzzy hybrid framework. Serdouk *et al*. [22] introduced a new gradient local binary pattern descriptor for signature characterization and Artificial Immune Recognition System for signature verification.

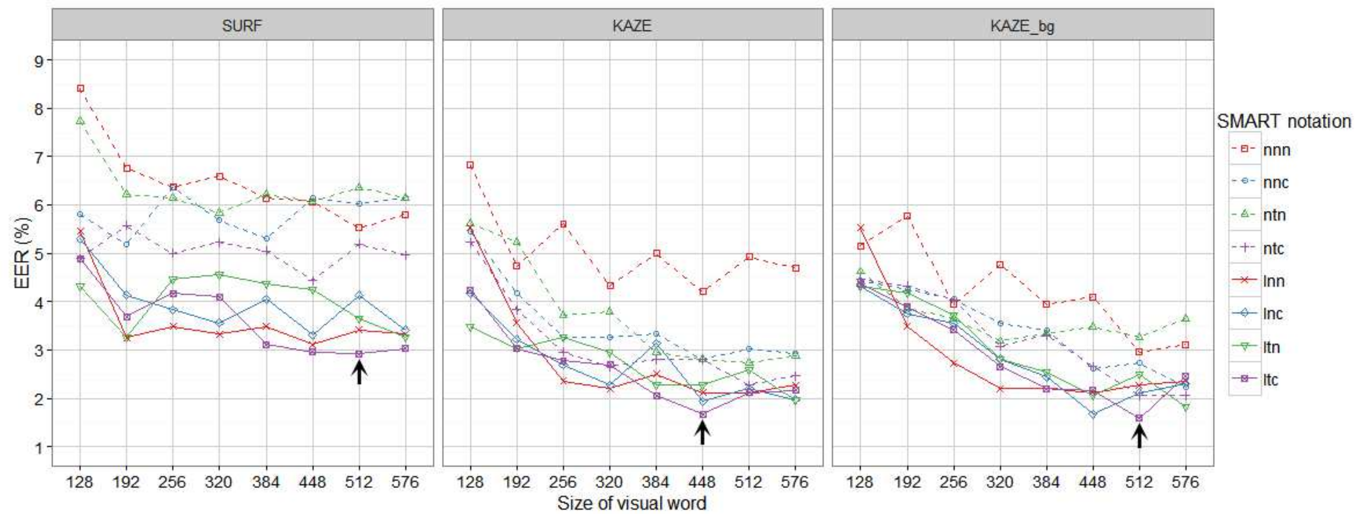


Figure 6. Effect of weighting schemes based on different types of local features. The arrows in this figure indicate the lowest EER when using the local feature. Here, "KAZE" shows the results using features detected in the strokes, and "KAZE_bg" shows those using features detected using both the strokes and the background space.

Table 2. Error rates of the proposed method compared to other systems using the CEDAR dataset.

References	Features	Classifier	#Signatures for training	Error rate (%)
[28] in 2004	Gradient, structural, and concavity	SVM	16 genuine + 5 forged	9.30
[23] in 2013	Local morphological pattern spectrum	Earth Movers Distance	15 genuine + 15 forged	9.58
[6] in 2013	Gradient direction histogram	Simplified Fuzzy ARTMAP	14 genuine + 14 forged	6.01
[22] in 2015	Gradient local binary patterns	Artificial Immune Recognition System	16 genuine + 16 forged	5.34
Proposed method	**BoVW with KAZE_bg_ltc**	**SVM**	**16 genuine + 16 forged**	**1.6**

It is difficult to compare the results as they are affected by the type or number of signatures during the classifier construction and the evaluation. However, Table 2 shows that the proposed method provides much lower error rates than the existing state-of-the-art signature verification methods.

5. Conclusion

The familiar use of handwritten signatures in various applications (*e.g.*, credit card authentication) increases the need for automated verification methods. This paper proposes a new offline signature verification method based on a BoVW model. The proposed method can be summarized as follows:

1. The use of cognitive processing of visual information by FDEs is considered to improve the offline signature verification performance.
2. To implement it, the BoVW model, in which local descriptors represent salient regions, is applied.
3. Experimental results show that weighting schemes on the BoVW model improve the performance, especially with the use of "ltc" in SMART notation.
4. Experimental results also show that KAZE features in the BoVW model further improve the performance compared to the popular SURF.
5. Additionally, the use of KAZE features from both strokes and the background space, to introduce the structures of not only strokes themselves but also of the relations between strokes, further promotes the performance.
6. Finally, the proposed method provides much lower error rates than the existing state-of-the-art signature verification methods using the CEDAR dataset.

Additional advantages of the proposed method are the flexibility to be applied even when a part of the signature is accidentally missing, and the resilience against attacks because the stored feature vectors based on the BoVW model do not directly reveal information about the original signatures.

Our future research plan includes the more practical use of the proposed method with an additional dataset, and improvements in the robustness by considering the individuality of writers.

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References

[1] P. F. Alcantarilla, A. Bartoli, and A. J. Davison. KAZE features. In *Computer Vision–ECCV 2012*, volume 7577 of *LNCS*, pages 214–227. 2012. 2, 3

[2] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool. Speeded-Up Robust Features (SURF). *Comput. Vis. Image Und.*, 110(3):346–359, 2008. 2, 3

[3] J. Coetzer, J. Swanepoel, and R. Sabourin. Efficient cost-sensitive human-machine collaboration for off-line signature verification. In *Proc. SPIE*, volume 8297, pages 82970J–82970J–8, Jan. 2012. 1, 2

[4] A. G. Dyer, B. Found, and D. Rogers. Visual attention and expertise for forensic signature analysis. *J. Forensic Sciences*, 51(6):1397–1404, 2006. 1, 2

[5] A. G. Dyer, B. Found, and D. Rogers. An insight into forensic document examiner expertise for discriminating between forged and disguised signatures. *J. Forensic Sciences*, 53(5):1154–1159, 2008. 1, 2

[6] G. Ganapathi and R. Nadarajan. A fuzzy hybrid framework for offline signature verification. In *Pattern Recognition and Machine Intelligence (Proc. PReMI 2013)*, volume 8251 of *LNCS*, pages 121–127. 2013. 5, 6

[7] A. Gilperez, F. Alonso-Fernandez, S. Pecharroman, J. Fierrez, and J. Ortega-Garcia. Off-line signature verification using contour features. In *Proc. 11th Int. Conf. Frontiers Handwriting Recognit. (ICFHR 2008)*, Aug. 2008. 4

[8] D. Impedovo and G. Pirlo. Automatic signature verification: The state of the art. *IEEE Trans. Syst., Man, Cybern., Part C: Applications and Reviews*, 38(5):609–635, 2008. 1, 2

[9] A. K. Jain, A. Ross, and S. Pankanti. Biometrics: A tool for information security. *IEEE Trans. Inf. Forensics Security*, 1(2):125–143, 2006. 1, 2

[10] E. Karakasis, A. Amanatiadis, A. Gasteratos, and S. Chatzichristofis. Image moment invariants as local features for content based image retrieval using the bag-of-visual-words model. *Pattern Recognit. Lett.*, 55:22–27, 2015. 1, 2, 3, 4

[11] J. S. Kelly and B. S. Lindblom. *Scientific Examination of Questioned Documents*. CRC Press, 2nd edition, 2006. 1, 2

[12] Y. Li, S. Wang, Q. Tian, and X. Ding. A survey of recent advances in visual feature detection. *Neurocomputing*, 149:736–751, 2015. 3

[13] D. G. Lowe. Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vision*, 60(2):91–110, 2004. 2, 3

[14] M. I. Malik, M. Liwicki, A. Dengel, and B. Found. Man vs. machine: A comparative analysis for signature verification. *J. Forensic Document Examination*, 24:21–35, 2014. 1, 2

[15] M. Okawa and K. Yoshida. Offline writer verification using pen pressure information from infrared image. *IET Biometrics*, 2(4):199–207, 2013. 1, 3, 4, 5

[16] M. Okawa and K. Yoshida. Text and user generic model for writer verification using combined pen pressure information from ink intensity and indented writing on paper. *IEEE Trans. Human-Mach. Syst.*, 45(3):339–349, 2015. 1, 3, 4, 5

[17] S. Pal, M. Blumenstein, and U. Pal. Off-line signature verification systems: A survey. In *Proc. Int. Conf. & Workshop Emerging Trends in Technology (ICWET 2011)*, pages 652–657, Feb. 2011. 1, 2

[18] S. Pal, S. Chanda, U. Pal, K. Franke, and M. Blumenstein. Off-line signature verification using G-SURF. In *Proc. 12th Int. Conf. Intelligent Systems Design and Applications (ISDA 2012)*, pages 586–591, Nov. 2012. 2, 4

[19] A. Pepe, D. Rogers, and J. C. Sita. A consideration of signature complexity using simulators' gaze behaviour. *J. Forensic Document Examination*, 22:5–13, 2012. 1, 2

[20] R. Plamondon and S. N. Srihari. On-line and off-line handwriting recognition: A comprehensive survey. *IEEE Trans. Pattern Anal. Mach. Intell.*, 22(1):63–84, 2000. 1, 2

[21] J. Ruiz-del Solar, C. Devia, P. Loncomilla, and F. Concha. Offline signature verification using local interest points and descriptors. In *Progress in pattern recognition, image analysis and applications (Proc. CIARP 2008)*, volume 5197 of *LNCS*, pages 22–29. 2008. 2

[22] Y. Serdouk, H. Nemmour, and Y. Chibani. An improved artificial immune recognition system for off-line handwritten signature verification. In *Proc. 13th Int. Conf. Doc. Anal. Recognit. (ICDAR 2015)*, pages 196–200, Aug. 2015. 5, 6

[23] B. Shekar, R. Bharathi, and B. Pilar. Local morphological pattern spectrum based approach for off-line signature verification. In *Pattern Recognition and Machine Intelligence (Proc. PReMI 2013)*, volume 8251 of *LNCS*, pages 335–342. 2013. 5, 6

[24] J. Sivic and A. Zisserman. Video Google: A text retrieval approach to object matching in videos. In *Proc. 9th IEEE Int. Conf. Computer Vision (ICCV 2003)*, pages 1470–1477, Oct. 2003. 1, 2, 3

[25] S. Srihari, C. Huang, and H. Srinivasan. On the discriminability of the handwriting of twins. *J. Forensic Sci.*, 53(2):430–446, 2008. 1, 2

[26] S. N. Srihari, S.-H. Cha, H. Arora, and S. Lee. Individuality of handwriting. *J. Forensic Sci.*, 47(4):856–872, 2002. 1, 2

[27] S. N. Srihari and K. Singer. Role of automation in the examination of handwritten items. *Pattern Recognit.*, 47(3):1083–1095, 2014. 1, 2

[28] S. N. Srihari, A. Xu, and M. K. Kalera. Learning strategies and classification methods for off-line signature verification. In *Proc. 9th Int. Workshop Frontiers Handwriting Recognit. (IWFHR 2004)*, pages 161–166, Oct. 2004. 1, 2, 4, 5, 6

[29] J. Unar, W. C. Seng, and A. Abbasi. A review of biometric technology along with trends and prospects. *Pattern Recognit.*, 47(8):2673–2688, 2014. 1, 2, 5

[30] V. N. Vapnik. *Statistical Learning Theory*. Wiley, 1998. 4

[31] Y.-J. Xiong, Y. Wen, P. S. Wang, and Y. Lu. Text-independent writer identification using SIFT descriptor and contour-directional feature. In *Proc. 13th Int. Conf. Doc. Anal. Recognit. (ICDAR 2015)*, pages 91–95, Aug. 2015. 2, 4